Optimizing Machine Learning Algorithms For Hyperspectral Very Shallow Water (VSW) Products

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LONG-TERM GOALS

This one-year effort will focus on the transition of FERI's machine learning algorithms for HyperSpectral Imagery (HSI) in the VSW into a distributable code set. This will provide a stable code platform for the application and transition of machine learning-based hyperspectral classification techniques into 6.3/6.4 programs.

OBJECTIVES

Our objective is to focus on three areas of application research and transitions. First, we will transition our machine learning-based algorithms and computer code for the determination of bathymetry, bottom type, and water column Inherent Optical Properties from HyperSpectral Imagery (HSI) into a deliverable Message Passing Interface (MPI) program that may be easily used by other research and military operators. Second, we will use this program to determine the impacts of the granularity of the classification database on the inversion bathymetry, bottom type, and IOPs. Third, we will move beyond the use of single pixel HSI inversion to the use of spatial context-filtering to remove pixel-to-pixel noise inherent in the HSI data.

APPROACH

Task 1

In previous works, a Look-Up Table (LUT) algorithm was used in accurately predicting bathymetry (Mobley et al. 2002, Bissett et al. 2004, Bissett et al. 2005, Mobley et al. 2005, Lesser and Mobley, 2008). The LUT approach is a subset of a larger body of artificial intelligence work concerned with algorithms and techniques that "teach" machine to learn from the examination of data and rules. This body of work is aptly called "machine learning" and some of its techniques include decision trees, genetic algorithms, and neural networks. The LUT approach is a subset of the k-Nearest Neighbor (kNN) algorithm, which is in the family of supervised learning algorithms.

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14. ABSTRACT
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Our use of the kNN algorithm maps a single HSI remote sensing reflectance vector, Rrs(λ), onto a database of estimated Rrs(λ). This database is created by providing the attributes of bathymetry, spectral bottom reflectance, and spectral IOPs to the radiative transfer routines of Ecolight (which is a high speed variant of Hydrolight, Mobley, 1994). We select the classification of the measured Rrs vector based on the best match of measured Rrs(λ) to estimated Rrs(λ). The LUT algorithm is based on a single best fit for our classification, i.e. k = 1. However, more recent work suggested that we could achieve a better classification by selecting a larger number for k, e.g. k = 50 (Bissett et al. 2006a). This larger number for k provides better accuracy and precision, as well as provides us with the ability to create confidence intervals for our classifications of bathymetry.

When classifying new spectra, the distance or angle between each measured spectrum and estimated spectrum in the database is calculated. The k nearest neighbors to that spectra (those having the smallest distances or angles), are considered sufficiently qualified to predict the corresponding attributes of bathymetry, bottom type, and IOP set. We have used the following metrics for the calculation of distance (Euclidean, Manhattan, Chebyshev, Canberra and Bray Curtis) and/or angle (Angular Separation and Correlation Coefficient). In general, our applications suggest that the Manhattan distance and the Correlation Coefficient angle metrics to be the best metrics to use for this algorithm. Once the set of nearest neighbors are determined, the attribute (e.g. bathymetry) of a pixel may be determined by a majority vote from the k nearest neighbor vectors. In the event of a tie, a prediction is made randomly from amongst the majority classes.

The computer code used in our creation of the estimated Rrs(λ) database and the spectral matching of the measured versus estimated Rrs(λ) is functional for scientific research; however it not well developed for transition for use by others in testing and evaluation applications.

The tasks of this project are as follows:

1) We will build upon our past research efforts to provide a Message Passing Interface (MPI) executable version of our kNN workbench for the inversion of hyperspectral imagery.

2) The code from Task 1 to rapidly test the impacts of granularity of attribute selection on the accuracy and precision of bathymetry estimated from our kNN code and the HSI data from Horseshoe Reef (Bissett et al. 2006b).

3) We will evaluate two types of context-filtering – (1) pre-filtering of the Rrs(λ) spectra before classification, and (2) context-filtering of the retrieved attributes after classification.

This year's work focused on Task 3 – context-filtering. The first type of context-filtering seeks to reduce the noise in Rrs(λ) spectra by replacing the spectrum value at each wavelength with the median value of the spectra in a spatial area surrounding the pixel of interest, say a 3 x 3 grid of pixels centered on the one of interest. This spatial filter is applied wavelength by wavelength. At wavelengths where Rrs(λ) is mostly signal, the final spectrum will not change by much. At wavelengths where Rrs(λ) is noisy, the noise in the surrounding pixels will tend to average out and the final spectrum values over the entire image area will be less noisy that the original.

The second type of context-filtering involves post-processing the retrievals themselves, rather than the original image spectra. In the case of real numbered attributes, such as bathymetry, we can apply a median filter to the retrieved depth. For bottom type and IOP set, the way forward is less clear. Each of these attributes is assigned a type with a specific vector (or set of vectors in the case of IOPs) of spectral values. How we filter "Dark Sediment" with "Sparse Vegetation" or "Highly absorbing and scattering waters #1" with "Case 1, chlorophyll a = 0.5 mg m^{-3}" will be a challenge. It may require some iterative solution that context-filters bathymetry first, and solves the kNN again using a constrained bathymetry solution approach. It may also be highly dependent on the granularity study in Task 2. These are the issues that we will address in this Task.

WORK COMPLETED

Task 3 starts with a baseline set of statistics with which to compare our spectral matching approaches to the "true" bathymetry measured with acoustical techniques. In addition to previously used estimates (see below), we include a new estimation of "spikiness" in the retrieval of bathymetry from our spectrum matching techniques. Spikiness, S, is defined in the depth estimates as follows. For a given pixel (i,j) with retrieved depth z(i,j), the average depth of the 4 neighboring pixels is

$$zavg4 = 0.25[z(i-1, j) + z(i+1, j) + z(i, j-1) + z(i, j+1)].$$

Spikiness, S(i,j), of the retrieved depth at (i,j) as the absolute percent difference in depth z(i,j) and zavg4,

$$S(i,j) = 100 \{|z(i,j) - zavg4|\} \text{ over } \{zavg4\}$$

For example at a kNN=1 (a single value LUT retrieval), if retrieval z(i,j) = 5 m or 15 m, and zavg4 = 10 m, then S(i,j) = 50%. Note that a linearly sloping bottom is the same as a level bottom as regards the value of zavg4. Thus a change in depth from one pixel to the next because of a sloping bottom is not recorded as spikiness. This metric is best suited for detecting a single spiky pixel. However, if a group of pixels is spiky, then some of the spiky pixels may be included in the zavg4 value, and the true spikiness may be underestimated for pixel (i,j). Likewise, a sharp change in bottom depth, e.g., due to a coral head, may be recorded as a depth spike even though the LUT retrieval is correct.

Other statistical measures for "goodness of fit" from previous efforts include –

1. The average percent difference in LUT vs acoustic depths (a negative/positive value means that the LUT depths are on average shallower/deeper than the acoustic depths)
2. The average difference in meters in LUT vs acoustic depths (a negative/positive value means that the LUT depths are on average shallower/deeper than the acoustic depths)
3. The standard deviation in meters of the LUT vs acoustic depths
4. The correlation coefficient, $r^{2,}$ between the LUT and acoustic depths
5. The percent of pixels for which the LUT depth is within ±1m of the correct depth
6. The percent of pixels for which the LUT depth is within ±25% of the correct depth

The baseline for our comparison of various selections of spatial filtering parameters and kNN parameters is seen in Figures 1. This figure show the bathymetry retrievals for unfiltered, kNN = 1 (LUT), parameters of our spectrum matching algorithms. In summary, we now have six quantitative measures of the overall accuracy of depth retrievals and two measures of the spikiness of depth retrievals. These metrics are used below to compare the effects of spatial smoothing of input Rrs spectra, of spatial smoothing of retrieved depths, and of the type of kNN analysis.

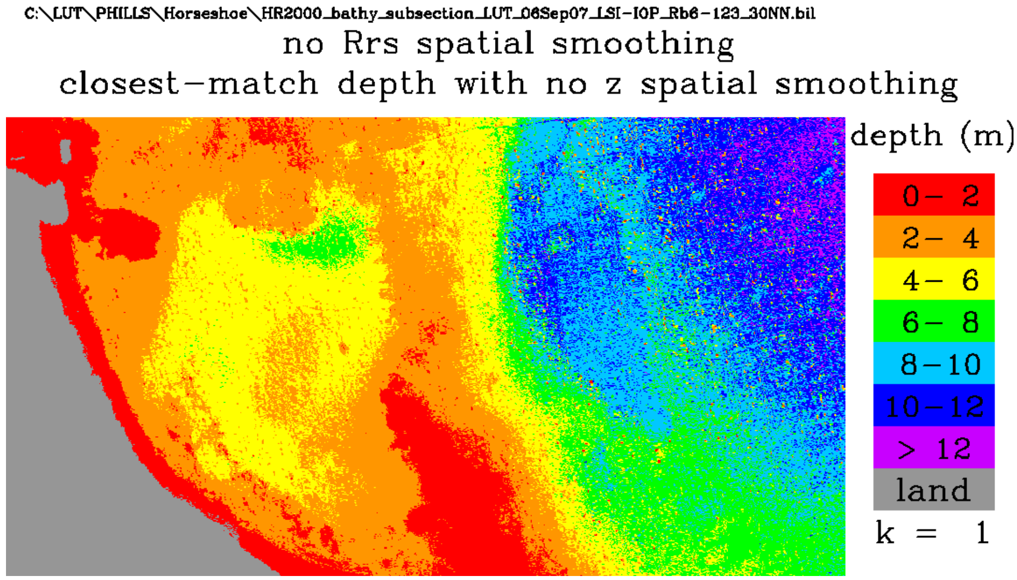

Figure 1. A 2D plot of retrieved depths, with the actual LUT-retrieved depths binned into 2-m bins. Even with the binning, there is noticeable speckle in the deeper waters at the upper right.

We created a matrix of combinations between for testing kNN, Rrs, and depth averaging yield a 3 x 3 x 3 solution matrix of 27 different combinations for analysis. The following list provides a brief summary of the results.

1. kNN analysis does not help if the input Rrs spectrum is bad
2. Using the median of k = 30 depths gives slightly better signed depth errors than does the average of 30 depths
3. Using the average of k = 30 depths gives somewhat less spikiness (smaller average S values, and fewer pixels with S > 25%) that does the median of k = 30 values
4. Other goodness-of-fit metrics are about the same for the average and median of k = 30 values
5. The average and median of k = 30 values give smaller signed depth errors (-0.8 to -2%) than does k = 1 (-7.0 to -7.4%), regardless of what smoothing is applied
6. The k = 1 depths give a smaller standard deviation of the LUT vs acoustic depth errors than does either the average or median of k = 30
7. smoothing of the retrieved depths reduces spikiness much more that does a corresponding (having the same value of n) smoothing of the Rrs
8. The average of k = 30 values reduces both average and extreme spikiness more than does the median

These results are very encouraging when compared to our baseline retrievals (Figures 4 – 7). However, there is no single "best" methodology that gives superior values for all error metrics.

Nevertheless, it appears that a reasonable recommendation (at least for the Horseshoe Reef image) is to:

1. use the median of k = 30 values to estimate the depth at each pixel (although using the average of k = 30 is about the same), which will give the most accurate average signed depth retrievals
2. definitely perform 3×3 or 5×5 spatial smoothing of the retrieved depths, which will greatly reduce the spikiness and thus further decrease the depth errors
3. optionally also perform 3×3 or 5×5 spatial smoothing of the Rrs spectra before doing the LUT matching (Figure 2 - 3)

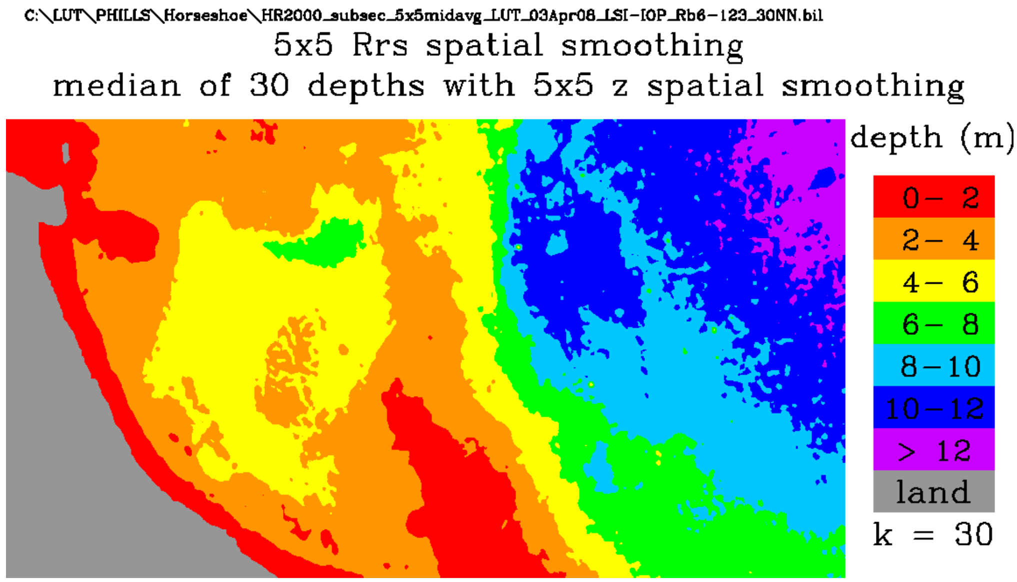

Figure 2. A 2D plot of retrieved depths, with the actual kNN-retrieved depths binned into 2-m bins and color-coded.

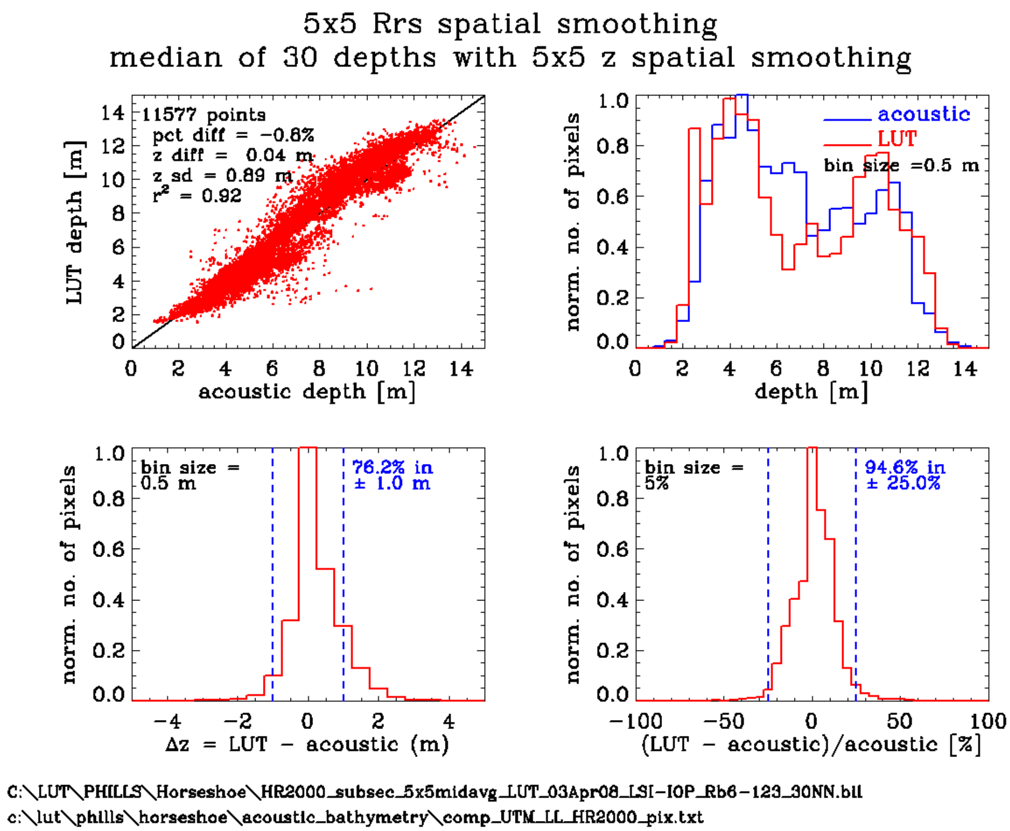

Figure 3. Goodness-of-fit results from kNN vs. acoustic depths for optional retrieval.

IMPACT/APPLICATIONS

This effort will deliver an application for testing and evaluating of our machine learning approaches to bathymetry estimation in Very Shallow Waters (VSW). While it is being demonstrated on hyperspectral imagery, the techniques and computer code may be used with any set of spectral reflectance data. As such the deliverables from this effort will allow other to create maps of depths, bottom types, and water clarity from a variety of airborne and space-based spectral sensors planned for operational deployment.

RELATED PROJECTS

This work is being conducted in conjunction with Dr. Curtis D. Mobley at Sequoia Scientific, Inc., who is funded under this effort for the collaboration as well as under other collaborative spectrum matching funding. These techniques developed here are now being applied to imagery of Australian coastal waters in a comparison of several different hyperspectral remote sensing algorithms for a variety of environments. That comparison study is being led by A. Dekker of CSIRO. The kNN algorithms developed under this grant are being transition within an application appliance to be delivered to Naval Oceanographic Office (N00014-09-C-0553) and is be delivered October 2009.

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